

## Online Gradient Descent

(Online Perceptron Algorithms)

$$f^{(t)}(\mathbf{w}) = \mathbf{w} \cdot \mathbf{x}^{(t)}$$

linear predictor (loss)

$$\ell(\mathbf{w}) = \frac{1}{\eta} \|\mathbf{w}\|_2^2$$

**Euclidean** regularization

$$\mathbf{w}^{(t+1)} = \mathbf{w}^{(t)} - \eta \nabla \ell(y^{(t)}, \hat{y}^{(t)})$$

**Additive** update

$$BL\sqrt{2T}$$

**No Regret**

## Online Exponentiated Gradient Descent

(Hedge/GWM, Winnow)

$$f^{(t)}(\mathbf{w}) = \mathbf{w} \cdot \mathbf{x}^{(t)}$$

linear predictor (loss)

$$\ell(\mathbf{w}) = \frac{1}{\eta} \sum_n w_n \log(w_n)$$

**Entropic** Regularization

$$\mathbf{w}^{(t+1)} = \mathbf{w}^{(t)} \exp \left( -\eta \nabla \ell(y^{(t)}, \hat{y}^{(t)}) \right)$$

**Exponential** update

$$\sqrt{(T/2) \log N}$$

No Regret